https://doi.org/10.1016/j.aei.2019.101008



# Smart Work Packaging-enabled Constraint-free Path Re-planning for Tower Crane in Prefabricated Products Assembly Process

***Xiao Li***, *Ph.D. Candidate, Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong, China. Email: shell.x.li@connect.polyu.hk*

***Hung-lin Chi***, *Ph.D. Corresponding Author, Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong, China. Email: hung-lin.chi@polyu.edu.hk*

***Peng Wu***, *Ph.D., Associate Professor, Department of Construction Management, Curtin University, Perth, Australia. Email: peng.wu@curtin.edu.au*

***Geoffrey Qiping Shen***, *Chair Professor of Construction Management, Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong, China. Email: geoffrey.shen@polyu.edu.hk*

## Abstract

Lack of constraint-free crane path planning is one of the critical concerns in the dynamic on-site assembly process of prefabrication housing production. For decades, researchers and practitioners have endeavored to improve both the efficiency and safety of crane path planning from either static environment or re-planning the path when colliding with constraints or periodically updating the path in the dynamic environment. However, there is a lack of approach related to the in-depth exploration of the nature of dynamic constraints so as to assist the crane operators in making adaptive path re-planning decisions by categorizing and prioritizing constraints. To address this issue, this study develops the smart work packaging (SWP)-enabled constraints optimization service. This service embraces the core characteristics of SWP including adaptivity, sociability, and autonomy to achieve autonomous initial path planning, networked constraints classification, and adaptive decisions on path re-planning. This service is simulated and verified in the BIM environment, and it is found that SWP-

enabled constraints optimization service can generate the constraint-free path when it is necessary.

**Keywords:** Crane Path Planning, Smart Work Packaging, Prefabrication Housing Production, Constraints Management, Building Information Modeling

## 1. Introduction

The situation of unbalanced public residential housing (PRH) supply and demand becomes more and more stringent in Hong Kong. According to the Housing Authority of Hong Kong (2019), there were more than 153,300 general applicants for PRH and the average waiting time for them was 5.5 years (highest in the last two decades). In order to expedite the supply of PRH, the PRH in Hong Kong has benefited and will continue to benefit significantly from prefabrication housing production (PHP), which is an innovative solution that the prefabricated material, component, module, and unit are manufactured efficiently at different locations and then converged at the site for installation (Li et al., 2017). The popularity of PHP, also known as modular integrated construction or prefabricated construction, is productively boosting the productivity of the construction industry of Hong Kong as it meets market demand for improving industry-wide performance in the aspects including fast-track process, alleviating the problem of on-site labor shortage, more sustainable and safer working environment (Wu et al. 2017). However, the supply of PRH is still plagued by the pathological schedule delay of PHP. For example, the government planned to construct 13,300 flat units of public housing in the financial year of 2016-2017. However, the actual completion was 11,276 units, meaning that delay occurred in 15.22% of the projects (Housing Authority, 2018). The uncertainties and constraints in the fragmented PHP process have proved to be the primary drivers (Li et al., 2018a). Uncertainty refers to something that may occur, whereas constraint (e.g., limited space and buffers) is something that will happen (Wang et al., 2016). The constraints are the obvious bottlenecks and thus are more predictable than the uncertainties to be removed in the task executions (e.g., four-day assembly cycle process). As such, reliable constraint-free schedules are vital for achieving an industrialized construction environment particularly in the on-site assembly process, which is central for delivering the final products (Li et al., 2017).

The reliability of PHP schedules can be improved via proactive constraints management, which is the process of modeling, optimizing, and monitoring of bottlenecks to ensure that work package-level tasks assigned to workers can be successfully executed (Blackmon et al., 2011). Managing constraints in PHP processes is to prepare more (e.g., detailed and dynamic planning with lean solutions) and act fast (e.g., on decision-making and collaborative working) using available information and knowledge. As such, the principal objective of constraints management is to continually improve the reliability of workflow by guaranteeing that precise information is always available at the right time in the right format to the right person.

As the tower crane leads the progress of site activities and makes it the hub of such PHP projects, overall performances including productivity and safety are constrained by smooth crane operations (Al Hattab et al., 2018). The "lack of collision-free path planning is considered as one of the most influential constraints to the on-site productivity, health, and safety of tower crane operations. Many studies have therefore focused on addressing this constraint by developing various simulations and algorithms to facilitate the path planning process in the construction field. For example, Sivakumar et al. (2003) adopted A* (a node-based optimal algorithm) to automate crane the path-planning task and found that A* search can provide near optimal paths. However, it was time-consuming. Ali et al. (2005) introduced the GA into the crane path planning to lessen the search time and enhance the quality of solutions. Chang et al. (2012) developed a method for near real-time path planning by using probabilistic roadmaps (PRM). As construction sites are complex and dynamic, smarter algorithms to incorporate the dynamic nature are also developed to improve the path re-planning. For example, Zhang and

Hammad (2012) improved the RRT by using real-time information deriving from sensory feedback to achieve the dynamic path re-planning. Chi et al. (2014) combined the PRM and A* as a balance mechanism between efficiency and solution quality to achieve path re-planning in a dynamic virtual environment. Cai et al. (2018) proposed a multiobjective master-slave parallel genetic algorithm to assist the path planning in narrow and dynamic high-dimensional spaces.

It should be noted that most studies in the field concentrate on developing an algorithm to generate a route when constraints occur in the path. These routes are then updated periodically or as a reaction to collision when there is any. To the authors' knowledge, there is no prior study that proposes a constraints optimization service for crane operators with decision-making mechanism related to re-generating crane path in a changing environment. Moreover, previous methods may not demonstrate the nature of a dynamic construction environment, as constraints vary over time, and thus the importance of moves will alter based on the situation of the current path (Han and Hasan, 2018). Namely, if the crane path is re-planned when it collides with constraints or over a specific time interval, the best time for replanning may be missed. Thus, there is an urgent need for an efficient approach to decide whether a path should be replanned or keep unchanged when the constraints dynamically change in a construction environment.

Thus, this study aims to develop an automatic path re-planning optimization service through smart work packaging (SWP) to assist the crane operator in computing path values with reference to specific constraints and deciding the necessity of path re-planning. SWP can be a piece of software that is able to assist the operator in accomplishing the lift tasks and is also made smart with augmented capacities of visualizing, tracking, sensing, processing, networking, and reasoning (Li et al., 2019). For example, crane operator's SWP can quantitatively assess the impact of workers in a crane's working area by computing the distance from the workers' smart work packages and then acquire path values to determine the necessity of path re-planning according to the changes in path values in a dynamic environment. The specific objectives of this study are (1) to develop a constraints optimization service for crane path re-planning when constraints occur over time; (2) to define, classify and prioritize a set of constraints that can disturb the crane path and instantiate these constraints into a physical construction site; (3) to enable decision making for smart path re-planning by using cost values (distance) from a path to a specific constraint; (4) to simulate the decision making results (e.g., whether shorter path exists, or path re-planning is needed) in a building information modelling (BIM) environment.

This paper is organized into the following sections. Section 2 demonstrates the results of the literature review. The SWP-enabled constraints optimization service is then established and presented in Section 3. Section 4 validated the proposed solution in the BIM environment. Section 5 provides a discussion of the results and Section 6 concludes the study.

## 2. Literature Review

### *2.1 Path Planning*

In prefabricated construction, manufacturers make continuous efforts to upgrade the design of prefabricated products, ranging from components (light-weighted products, e.g., facade) and modules (large and heavy products, e.g., volumetric precast bathroom) to pre-acceptance integrated units (larger and heavier products with finishes, fixtures, and fittings) (Han et al., 2014). Given the development of prefabricated products, cranes, with their excellent transportation capacity, have a decisive role in the assembly of prefabricated products by lifting them vertically and horizontally after production (Han et al., 2014). As such, the constraint-free path of the crane is a crucial factor for safety and productivity, particularly in the PHP construction site of Hong Kong due to the high level of congestion. Presently, cranes operators execute lifting tasks based on their knowledge and limited site perception. This intuitive manipulation can usually lead to inefficient and unsafe operations (Kang et al., 2009). Although the duration of inefficient operations in one assembly cycle may be short, inefficient operations can waste a compelling amount of time when the hundreds or thousands of assembly cycles are to be conducted in a PHP project (Kang and Miranda, 2008). Path planning has frequently been required in various fields (e.g., air, land, underwater) to provide the safe route from the start to the end point with optimized costs (e.g., time, motion, distance, and energy) (Cai et al., 2018). Additionally, it is recurrently inevitable to replan a path under the dynamic environment. Previous studies have focused on developing various simulations and algorithms to facilitate the path planning process in the field of robotics. These include sampling-based algorithms (e.g., rapidly-exploring random trees (RRT), probabilistic roadmaps (PRM)) (Zucker et al., 2007), node-based optimal algorithms (e.g., Dijkstra, A*, D*) (Koenig and Likhachev, 2005), bioinspired algorithms (e.g., genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO)) (Zhang et al., 2016), and mathematic model-based algorithms (e.g., mixed-integer linear programming) (Yilmaz et al., 2008). The robotic motion planning methods are the mainstream approaches for developing crane path-planning algorithms to achieve constraint-free travel, where cranes can be generally considered as multiple-degree-of-freedom (DoF) (e.g., 3 DoF for tower crane) robotic manipulators (Lei et al., 2013). The studies to date for crane path planning (See table 1) have concentrated primarily on developing algorithms and computer-aided tools to generate feasible or optimal paths in the offline (pre-processed) or online (real-time) manner. Although some studies have also made efforts to enhance the dynamic path re-planning of the crane through reducing the computational time and improving path quality when certain unpredictable constraints occur (AlBahnassi and Hammad, 2011; Zhang and Hammad, 2012; Chi et al. 2014), they did not draw attention to whether the path should be re-planned or remain unchanged when the constraints change dynamically in the construction site. Thus, an innovative decision-making approach for path re-planning in a dynamic construction site by computing path cost values according to the importance and implications of these constraints is imperative.

<Insert Table 1>

## *2.2 Constraints Management*

Constraints management (CM) is one of the critical strategies for production control and planning. The concept of constraint was firstly introduced in 1984 as the theory of constraints (TOC) which is a management philosophy for identifying the most critical bottleneck that prevents achieving a goal and then systematically improving the constraint until it is no longer the bottleneck (Goldratt and Cox, 1984). It assumes that each intricate system may comprise multi-connected activities, and there is at least one activity acts as a constraint in the fully connected system (e.g., the constraint activity is the "weakest link in the chain"). And the entire process throughput can only be maximized when the constraint is improved. A corresponding deduction is that spending more time on optimizing non-constraints activities cannot generate significant benefits, and only improvements to the constraint will reach the goal. Thus, TOC aims to offer an accurate and continuous focus on improving the current constraint until it no longer confines the goal, at which point the focus moves to the next constraint. Constraints management systems have proven to be more effective when compared to the reorder-point systems and material requirements planning systems in the aspects of capacity management, inventory management and process improvement in the manufacturing industry. It is also argued that constraints management can outperform the Just-in-time system owing to the more targeted nature of improvement efforts in constraints (Boyd and Gupta, 2004). The construction industry has widely recognized the significance of performing detailed control and planning with constraint management to issue executable work plans. For example, the constraints management process including constraint modeling, optimization, and monitoring have been proposed in previous studies (Li et al., 2019). Constraint optimization aims to optimize the task execution by improving the constraints in its operation process. However, current constraints in PHP processes are dynamic in either physical aspect or informational aspect (Gong et al., 2019). This study will make efforts to improve the specific dynamic constraints which physically (e.g., moving obstacles) prevent successful lifting task.

### *2.3 Smart Work Packaging*

Proposed by Li et al. (2019), smart work packaging (SWP) is an innovative approach for operations or task executions that are made smart by integrating augmented capacities of visualizing, tracking, sensing, processing, networking, and reasoning so that they can be executed autonomously, adapt to changes in their physical context, and interact with the surroundings to enable more resilient process. Instead of introducing an entirely novel system to PHP sites, an SWP-enabled operation system relies on smart construction objects (SCOs) (e.g., prefabricated products and human resources equipped with RFID tags) and internet-of-things (IoT) enabled BIM platforms, which have already been involved in the on-site assembly process of PHP (Niu et al., 2015; Li et al., 2018b). Without compromising existing informational objects and platforms, these SWPs are augmented with smart and interconnected properties to assist operations. For example, a smart crane path planner can be able to make decisions that whether there is a need for path re-planning by retrieving/computing the location/distance information of the dynamic constraints from informational objects and platforms. The three core characteristics of SWP, adaptivity, sociability, and autonomy refer to SWP's abilities in responses to changes, information exchange, and action-taking, respectively (Li et al., 2019). Each core characteristic is further classified into sub-properties with different level of functions (exemplified by a tri-axial graph and interpretative table in Figure 1), the exploitation of which allows the potentials of SWP for task executions to be achieved. The decision-making mechanism needed in the path re-planning for this study is also the trial to activate the potential of resilience in SWP's adaptivity. The most distinct feature of

SWP compared with traditional PHP work packaging method, denotes SWP's ability to have a positive response to change, and learn from their own experiences, environment, and interactions with others. This characteristic is based on the concepts of smart workflows proposed by Wieland et al. (2008), which includes three dimensions, e.g., robustness, flexibility, and resilience (Husdal, 2010). Resilience is a high-level adaptivity that facilitates SWP to survive unforeseeable changes (that have severe and enduring impacts) in a dynamic replanning manner.

<Insert Figure 1>

# 3. Methodology

## *3.1 SWP-enabled Constraints Optimization Service*

In this study, an SWP-enabled constraints optimization service is proposed. The architecture of this service is shown in Fig.2. This service is supported by the smart construction objects (SCOs) and smart BIM platform (Li et al., 2019). The SCOs are built by equipping the dynamic site objects (potential external constraints) such as cranes, crews, vehicles, and prefabricated products with various sensing and tracking technologies (e.g., RFID, sensors for monitoring wind speed and rain load, WiFi, camera, and laser) for achieving smartness in data generation and collection. This process can both enrich and exchange the information with smart BIM platform. After the informational interactions between crews and virtual BIM platform/SCOs, the characteristics (e.g., adaptivity, sociability, autonomy) of smart work packaging (SWP) can be activated to execute the tasks through different services. A generic workflow for SWP-enabled constraints optimization service can be outlined in Fig.3. Firstly, the As-is construction environment and existing constraints can be detected and built into the BIM environment in the crane operator's smart work package. This can activate the autonomy properties to facilitate the SWP to autonomously generate the initial path planning and visualize it for the crane operator. Then, SWP can activate the sociability properties by communicating with SCOs to detect the dynamic constraints and prioritize their importance. These dynamic constraints may include other moving cranes with overlapping operation area (critical), moving crews/vehicles in the crane operation area (non-critical & non-ignorable), normal wind/rain (non-critical & ignorable). The locational information of these dynamic constraints is collected to calculate the distances between constraints and loads. These distances can be used to update the cost values of the original path. Finally, the adaptivity property can be activated to decide whether a path re-planning should be conducted. To develop the initial path planning, constraints classification, and decision on path re-planning in this workflow, several assumptions, and problem formulations are presented in the following sections.

<Insert Figure 2>

<Insert Figure 3>

### *3.2 Assumptions*

Inspired by the methods in Han and Hasan (2018), and Chi et al. (2014), a resilient decision-making approach in SWP of crane operator can be developed for crane path re-planning in a dynamic construction environment through using path cost values that diffused from a specific group of constraints. Accordingly, several assumptions should be proposed:

(1) The roadmap graph in Configuration space (C-space) is displayed on a three-dimensional grid that composed by the equidistant cubes. The path planning method proposed in this study is built on the Probabilistic Roadmap (PRM), which equidistant geometrical points are sampled and connected (including the start and goal point) in the C-space. The process of PRM can be usually shown in Figure 4 (Chi et al., 2014). The graph structure G in C-space can be formulated as:

$$\mathrm{G} = (v, e) \qquad (1)$$

<Insert Figure 4>

Where *v* is the vertex that represents each geometrical point, and *e* is the edge that connects the vertexes. Because the roadmap graph is assumed to be a three-dimensional equidistant cubic grid, the connections between vertexes are the sides or diagonals of cubes. In order to identify loads of a tower crane in the sampled grid, the C-Space transformation is adopted (Chi et al., 2014). As shown in Figure 5, the location of the loads can be transformed from Cartesian space ($X$, $Y$, $Z$) to the 3-DOF tower crane's configuration ($\theta$, $\gamma$, $l$), where $\theta$ denotes the rotation angle of the crane turntable, $\gamma$ stands for the rotation radius of the crane jib along with the distance between the current trolley and the mast, and $l$ means its current hoisting distance between jib and hook. All the motions of the crane can be transformed into a point in the C-space. However, crane operators usually can only maneuver 2-DOFs of a tower crane together (Chi et al., 2014). For example, although rotating the jib while hoisting the loads can reduce the operation time, they are limited by the perception capacity of operators. This situation is not considered by the PRM, which may allow the generated path by PRM to be infeasible in practice. Even though the planned path is feasible to operate, the crane operator needs to be very cautious on extra DOFs that may exceed the operator's perception capacity of human manipulation (e.g., control sticks) and lead to risks in safety and schedule. To deal with this issue, the cubic grid sampling method is proposed in C-space. Take Figure 6 as an example to illustrate the rationale, sampling points are linked horizontally for a single DOF configuration, and vertex can be connected diagonally for a 2-DOF configuration. The sides of the cubic can only be connected between neighboring points.

<Insert Figure 5>

<Insert Figure 6>

(2) The dynamic constraints occur in a known construction environment. It means that the points of start and end are known and pre-determined, and dynamic constraints can move in any direction at any speed. Each constraint in Cartesian space transforms to the various polygons overlapped on the grid vertexes in the C-space (See Fig.6), which is C-obstacle. The C-obstacle denotes a cluster of motion ($\theta$, $\gamma$, $l$) of tower crane must be avoided.

(3) A load of crane moves one side or one diagonal of the square for each time interval. The notation for this study has been listed in Table 2. The runtime is represented as $T$, which also denotes the movement times due to the assumption that one move is generated during each time interval. A path $P_T$ can be defined according to $T$, and $v^{t,T}$ can be denoted as a set of grid vertexes near the path $P_T$ that from the current vertex to the goal vertex. Variable $t$ represents grid vertex order in $P_T$ as $t = \{1, 2, \ldots, N_T\}$ where $N_T$ signifies the count of grid vertexes from the current vertex to the goal.

<Insert Table 2>

## 3.3 Problem Formulation

After the establishment of the above assumptions, the constraint-free path re-planning in this study can be considered as an optimization problem which contains two stages: initial path planning and path re-planning decision-making.

### *3.3.1 Formulation of initial path planning*

The initial path planning is to detect the optimal edge combinations from the start vertex to the goal vertex based on the condition of initial constraints. The distance of the cubic edge (the connection between two vertexes, e.g., side and diagonal) indicates the unit of cost value, and the optimal path is to search for the route with minimum cost values. Compared with Dijkstra's algorithm that is time-consuming to assess all edges of the grid to find an optimal solution, A* search algorithm with a partial heuristic function can help balance efficiency and performance for evaluating the quality of current solutions and removing impossible paths during search processes (Chi et al., 2014). The formula is shown in Equation (2):

$$f(T) = \mathrm{g}(T) + h(t) \qquad (2)$$

Where g($T$) denotes the function computing the precise cost values from the starting vertex to the current vertex and $h(t)$ stands for a heuristic estimate function to estimate the predicted cost values from the current vertex to the goal. In addition, detection of initial constraints is an essential part of initial path planning, and it can guarantee each part of the path does not collide with neighboring constraints in the C-space. The paths obstructed by constraints may provide inoperable guidance for operators. The collisions can be identified by the ray tracing method, which check whether the two vertexes of a side can "see" each other or not (Chi et al., 2014).

*3.3.2 Formulation of path re-planning*

The path re-planning decision-making process starts with the categorization of constraints according to their priorities and positions, rather than treating all constraints uniformly. Through the interviews of six senior crane operators and four crane coaches in the crane training center of HK Institute of Construction, the classification for dynamic constraints of crane path planning is proposed from aspects of internal and external aspects, as can be seen in Table 3. The movements of constraints can lead to changes in the distance between the planned path and specific constraints. These changes are recorded by the cost values of the path, which are computed by the diffusion of specific constraints. Decisions of path re-planning are then made according to the dynamic differences in cost values of the path.

<Insert Table 3>

*(1) Formulation of constraints and cost value*

All constraints can be classified and defined based on the priority listed in Table 3 to form the categorization in Table 4. To define each sub-class of constraints accurately, for $c_i \in C$, let the shortest path at $T$ be $P_T^{-c_i}$ and $P_T^{-C}$ for the situations where $c_i$ does not exist or where a complete constraint does not exist, respectively. Additionally, allow a function $Z(\bullet)$ return one if there are more than one intersection between a constraint and a path, otherwise zero.

<Insert Table 4>

Critical constraints (*CC*) is a group of constraints that will collide with both $P_T^{-c_i}$ and $P_T^{-C}$ as in Definition 1. Definition 2 defines that non-critical constraints (*NCC*) is a group of constraints by deducting *CC* from *C*, which signifies that $CC \cup NCC = C$ and $CC \cap NCC = \emptyset$ . NCC can be classified into $NCC^{NI}$ and $NCC^{I}$ according to whether the constraint is ignorable or not when conducting the re-planning. $NCC^{NI}$ and $NCC^{I}$ can be defined as groups of constraints that collide with $P_T^{-c_i}$ and do not collide with $P_T^{-c_i}$, respectively. It indicates that $NCC^{NI} \cup NCC^{I} = NCC$ and $NCC^{NI} \cap NCC^{I} = \emptyset$.

After the definition of different constraints, the numerical influence of *CC* and $NCC^{NI}$ on a path can be computed by considering them as objects that diffuse influence (See Figure 7). All feasible grid vertexes can obtain the influence values from *CC* and $NCC^{NI}$. The larger influence values (smaller cost values) are attached to vertexes near *CC* or $NCC^{NI}$, while smaller influence values (larger cost values) are attached to vertexes that are distant from *CC* or $NCC^{NI}$. This influence diffusion process assumes that $NCC^{I}$ does not affect the path. Also, the grid vertexes on constraints can be treated as infeasible vertexes which the influence values are shown as "Inf."

<Insert Figure 7>

To define the detailed process of cost value diffusion (the below context will use cost value instead of influence value for consistency) from *CC* and $NCC^{NI}$, let the cost values from *CC* and $NCC^{NI}$ attached to vertex *v* be represented as $U_{CC}(v)$ and $U_{NCC^{NI}}(v)$, respectively, and let $V_{CC}$ and $V_{NCC^{NI}}$ be lists of vertexes that already acquire cost values diffused from *CC* and $NCC^{NI}$, respectively. As the process of cost value diffusion is the same for $CC$ and $NCC^{NI}$, Eqs. (3)-(6) take $CC$ as an example to formulate its cost value diffusion process. For all other vertexes not yet attached cost values from $CC$ or $NCC^{NI}$, a set of vertexes adjacent to $v_f$ are $A$ ($v$), which can be defined in Eq.(3)

$$A(v) = \left\{v' \middle| \left\|v' - v_f\right\| \leq l, \forall v' \in \left\{V_f \backslash V_{CC}\right\}\right\} \quad (3)$$

Where $l$ is the edge length of each square (side or diagonal). Diffusion is implemented by attaching a cost value increased by $\sqrt{2}$ or 2 from the current value on adjacent vertexes on the sides or diagonals of the square. Then, $V_{CC}$ and $V_{NCC}{}^{NI}$ are updated. As soon as $A$ ($v_f$) obtains cost values, $A$ ($v_f$) turns into $v_f$ for the next diffusion. Eqs. (4)-(6) are repeated until all $v_f$ acquire cost values, which means that diffusion is completed and then $V_{CC}$ or $V_{NCC}{}^{NI}$ becomes the same as $V_f$.

$$U_{CC}\left(A(v_f)\right) = U_{CC}(v_f) + \sqrt{2} \text{ or } U_{CC}\left(A(v_f)\right) = U_{CC}(v_f) + 2 \quad (4)$$

$$V_{CC} = V_{CC} \cup A(v_f) \quad (5)$$

$$v_f \leftarrow A(v_f) \quad (6)$$

*(2) Formulation of dynamic scenarios*

Figure 7 demonstrates the cost value diffusion process on the roadmap with two, one, and one constraint in $CC$, $NCC^{NI}$, and $NCC^{I}$, respectively. The cost values determined by $CC$ and $NCC^{NI}$ can be represented with the form ($U_{CC}$ ($v$), $U_{NCC}{}^{NI}$ ($v$)). There is no diffusion around $NCC^{I}$ because it is not an object with the capacity of diffusing influence. The decision to re-plan a path depends on the continuation of alterations in the cost values of the path, and the cost values are calculated by the diffusion process from $CC$ and $NCC^{NI}$. Namely, when constraints move, the changes in the path cost values caused by $CC$ and $NCC^{NI}$ are observed through moving constraints, and a decision on re-planning the path is made according to this observation. To clarify the changes in cost values in various situations, six scenarios are proposed in Table 5.

<Insert Table 5>

The cost values attached to $P_T$ from $CC$ and $NCC^{NI}$ can be denoted as $U_{CC}(P_T)$ and $U_{NCC}{}^{NI}(P_T)$, respectively. In these six scenarios, $l$ is believed to be adequately small to assess the need for path replanning from the changes in cost values caused by the dynamic constraints. Actually, If a collision between constraints ($CC$ or $NCC^{NI}$)and $P_T$, it is apparent that the current solution ($P_T$) is an infeasible path. Therefore, $U_{CC}(P_T)$ and $U_{NCC}{}^{NI}(P_T)$ display "Inf" in overlaying vertexes. The decision is made to re-plan due to a change in cost values of the path. Conversely, if there is no-collision, changes in cost values of path rely on the situations that group of constraints moved. Thus a decision can be made to replan a path when the current path can be improved in cost values, which will be illustrated in the following six scenarios.

In scenarios 1 and 2, if the movement distance of constraints in $CC$ is $d \geq l_s$, $U_{CC}(P_T)$ will be updated, and $P_T$ is no longer the optimal path. Given $N$ as the length between current and goal vertexes, $N$ is the minimum value of the path length, and $CC$ can make the new path to be longer than $N$. As a consequence, the new path is generated by surrounding the constraints in $CC$. The path collides with $CC$ represents an infeasible solution, and $U_{CC}(P_T)$ reflects this infeasibility with the value of "Inf." Since the changes have shown in cost values of the path, a decision should be made to re-plan the path. Even though there is no collision by the movement of $CC$, a change to $U_{CC}(P_T)$ occurs, indicating the necessity of path re-planning due to the improvement of $P_T$. Thus, scenarios 1 and 2 signify that the movement of $CC$ leads to the path re-planning, and the current path surrounding $CC$ is neither the shortest path nor a feasible option.

In scenarios *3* and *4*, $U_{NCC}{}^{NI}(P_T)$, similar to $U_{CC}(P_T)$, changes with the movement of constraints in $NCC^{NI}$ : $d' \geq l_s$ regardless of whether a collision occurs and $P_T$ will not be the shortest path.

Regarding the relative positions of constraints and $P_T$, each constraint $c_i$ in $NCC^{NI}$ can either encircle or be far away from $P_T$. $P_T$ is far away from $c_i$ if a path that detours around $c_i$ is assessed as a shorter path; otherwise, it encircles $c_i$. Thus, there are two situations in scenarios *3* and *4*: (i) When $P_T$ encircles $c_i$ in $NCC^{NI}$ and $c_i$ moves, it is the same as scenarios *1* and *2* that $c_i$ makes the path longer than *N*. Thus, the result is the same as scenarios 1 and 2 ; (ii) When $P_T$ is far away from $c_i$ and $c_i$ moves, although there are changes in $U_{NCC}{}^{NI}(P_T)$, it cannot be concluded that $P_T$ is not the optimal one. It highly relies on the size and shape of the constraint and the direction of movement.

In scenario *5* and *6*, regardless of whether or not the collision occurs between $P_T$ and $c_i$ after $NCC^I$ moves, $U_{NCC}{}^{NI}(P_T)$ and $U_{CC}(P_T)$ remain unchanged, since $NCC^I$ is not an object for cost diffusion. And the colliding parts of $U_{NCC}{}^{NI}(P_T)$ and $U_{CC}(P_T)$ will not become "Inf" when a collision occurs. Therefore, $P_T$ is still the optimal solution. $NCC^I$ is defined as a group of constraints that do not disturb the planned path.

Finally, the algorithm of decision-making for path re-planning in a dynamic environment can be illustrated summarized in Table 6.

<Insert Table 6>

# 4. Simulation Verification

## *4.1 Simulation Design*

To test the performance of the proposed path re-planning approach, a simulation-based constraints optimization service was developed and demonstrated in the BIM environment. This service is developed on the cross-platform game engine named Unity 3D, which offers the scripting application programming interface (API) in C# with inbuilt physics library to simulate the crane operation tasks, on-site assembly environment, and dynamic constraints.

The implemented algorithms include modified PRM method (sample equidistant cubics), A*, and *SWP_PathPlanner*.

To normalize the path value, the distance transform method is adopted and the fitness value of a path at $T$, $F(P_T)$, is computed as the distance between the immediate start vertex $v^{1,T}$ and the goal $v^{N_T,T}$, as shown in Eq.(7). Furthermore, the distance can also be calculated as the product of the edge length of each cube $l$ ($l_s$ or $l_d$) and $N_T$ (the number of edges in $P_T$).

$$F(P_T) = \sum_{t=1}^{N_T-1} \|v^{t,T} - v^{t+1,T}\| = l \cdot N_T \tag{7}$$

This study designs a virtual on-site assembly environment in the Unity 3D (See Figure 8). A 2-DOF tower crane, 13 dynamic constraints including tower crane operating near the targeted one (A), workers walking around the site (B1, B2, B3, B4), workers operating forklift (C), workers working at fixed position (D1,D2,D3), Dump trucks (E1,E2,E3), normal wind/rain (F), and an under-constructed prefabricated building (BIM model) are set up. The movement of the tower crane is guided by the suggested path, and the six scenarios with critical constraints (A), non-critical & non-ignorable constraints (B,C,D,E), and non-critical & ignorable constraints (F) defined in Section 3.3.2 are simulated in the BIM environment. The size of this roadmap graph is [360°, 50 cm, 50 cm] under the configuration coordination system, and the edge lengths of 1-DOF and 2-DOF are set to $\sqrt{2}$ cm and 2 cm, which leads to a total of 900,000 grid vertexes in the roadmap graph. The start ((23.4, 2.4, 1.3), Cartesian coordinates) and the goal ((-6.0, 20.8, 2.1), Cartesian coordinates) are the real lifting and placing point in the BIM environment. Their configuration coordinates of the start and the goal are (4, 27, 24) and (161, 9, 17).

Each constraint moves with random distance and direction in a specific iteration except that the movement distance should be a multiple of $l$. Additionally, to meet the real situation, the shape of constraints represented in the 3D roadmap graph without any restrictions rather than must overlap with grid vertexes showed in the methodology part.

### *4.2 Simulation Results*

Figure 9 demonstrates the original environment, dynamic environment, and the environment with the decision for each scenario in the roadmap graph of BIM environment, where the probability of movement for each constraint is random. (1) In the set of figures for the original environment, the blue dashed line is the shortest path without constraint ($P_T^{-C}$) and the green dashed line represents the shortest path after the cost value diffusion process ($U_{CC}(P_T)$ and $U_{NCC}^{NI}(P_T)$ ). Constraints in *CC* and $NCC^{NI}$ are attached with the matching entity name and ID in the BIM environment. (2) In the set of figures for the dynamic environment, dynamic and static constraints are also attached with the matching entity name and ID in the BIM environment. Dynamic $U_{CC}(P_T)$ and dynamic $U_{NCC}^{NI}(P_T)$ are updated on the yellow dashed line. (3) In the set of figures for the environment with the decision, the comparisions of path values are conducted and the path is re-planned if any difference occurres. The new path is demonstrated by a red dashed line.

In general, the results show that the crane lifting task can be completed from the start to the goal with 66 movements (*T*). The total number of the dynamic constraints for all iterations was 13. In each *T*, the minimum, maximum, and an average number of dynamic constraints were 1, 5, 11. Path re-planning conducted 4 times in the 66 movements (*T=9,11,22,34*) signifying that path re-planning was not essential for each *T*, even when more than 85% dynamic constraints existed at each *T (e.g., T=10, scenario 4-1)*. The detailed results corresponding to the six scenarios are discussed in the following.

<Insert Figure 9>

(1) In $T$=*34,* scenario 1 can be validated by the evidence that another crane A in $CC$ collided with the path resulting in the change of the path values and path re-planning. Contrarily, scenario 2 is simulated in $T$=*23*. It shows that another crane A in $CC$ became more distant from the path, and there was no collision, but it also led to path values changed and re-planning.

(2) In $T$=*9,* scenario 3 occurred that moving crews and vehicles (B,C,D,E) in $NCC^{NI}$ collided with the path and the result is the same as the scenario 1. However, the scenario 4 happened in $T$=*12* (path value changed and path re-planned, scenario 4-2) and $T$=*8* (path value changed and keep the original path, scenario 4-1) was totally different because it depended on whether the moving crews and vehicles were surrounded or distant from the path.

(3) In $T$=*6* and $T$=*5,* scenario 5 and 6 are assessed to show that there was no path re-planning regardless of whether the normal wind and rain in $NCC^{I}$ collided or did not collide with the path.

# 5. Discussion

Smart work packaging (SWP), with its core characteristics of adaptivity, sociability, and autonomy, offers a new insight to resiliently optimize the constraint-free crane path re-planning in the on-site assembly process of PHP. Compared with the previous crane path re-planning approaches used in the construction environment with dynamic constraints, SWP-enabled constraints optimization service for dynamic path re-planning is expected to have better performance in the following aspects. *SWP-PathPlanner* can avoid unnecessary crane path re-planning compared with the method of periodical path re-planning which conducts the re-planning at each specific time interval. The latter may have more computational cost since it updates more frequently (Chi et al., 2014). *SWP-PathPlanner* may not miss the shortest paths compared with the method of re-planning when collided, because it conducts the re-planning only when meeting with constraints. The latter may lead to longer paths and more crane operations (Zhang and Hammad, 2012). Another important distinguishing feature of the SWP-enabled constraints optimization service is to instantiate the various dynamic constraints considering the practical crane operations in the construction environment. Existing studies on dynamic robot path re-planning have investigated the numerous dynamic path planning methods in a theoretical manner (Han and Seo, 2018; Zhang et al., 2016). This study, however, has shown that the panoramic and interconnected characteristics of SWP can not only autonomously generate the path and detect/classify the constraints in a networking manner but also make adaptive decisions on the path re-planning.

Several innovations of this study can also be highlighted. Firstly, SWP demonstrates a new workflow to optimize the task execution level constraints using an example of crane path planning. Although not all constraints for the crane path planning process are investigated, the lean philosophies in constraints classification (prioritizing) and the smartness in designing optimization mechanism can be considered as a useful example for dealing with other constraints. Secondly, SWP-enabled constraints optimization service does not try to change the current crane operation habits of the operators, but to make them smarter for improving the bottlenecks particularly the dynamic ones. Additionally, a digital environment, assuming all data generated from sensors are well used, is integrated into the SWP to help guide the operators in advance for path planning in numerous situations such as in training.

This study has initiated the work of introducing smart construction objects (SCOs), work packaging, digital twin, edge computing, and lean philosophies to constraints management of PHP (See Fig.10). By modeling the constraints in the on-site assembly process, their interrelationships and the critical constraints can be identified. However, constraints usually are dynamic, and it would be complicated to optimize them by only adopting emerging technologies. The SWP-enabled constraints optimization service take advantages of both SCOs in data generation and work packaging in providing value-added information to offer more efficient decision making for constraints optimization. The results show that smart work packages can not only help optimize internal constraints but also be used as a platform to further integrate other concepts to improve project performance such as schedule, Just-in-time delivery, and site/buffer layout.

It may be argued that the SWP-enabled constraints optimization service is too ambitious and impractical in real crane operations. The fact that the adaptivity of this smart service is verified in a virtual environment should not be considered as a limitation of this study. Since the characteristics of these dynamic constraints simulated in this virtual environment can reflect the real situation in the on-site assembly process of PHP. However, there is still room to improve the validation prat of this study in the following aspects. For example, the quantative comparision with the approaches of re-planning when collided and periodically re-planning in every T can be conducted. And the probability of each constraint movement and the number of grid vertexes (namely the density of the grid, which can be zoomed through the edge length of each cube) can also be varied in the simulation process to see the disadvantages and advantages of these approaches under different dynamic scenarios.

<Insert Figure 10>

# 6. Conclusion

This study provides an in-depth exploration of smart work packaging (SWP) in constraints optimization that concentrates on smart decisions with adaptivity in path re-planning under a dynamic crane operation environment. Deviating from traditional methods that are re-planning a lift path when the current path collides with constraints or over a specific time interval, this study argues for the adaptivity of SWP with a decision-making mechanism to update a path when necessary. By augmenting existing task execution process of crane path planning with the core characteristics of SWP including adaptivity, sociability, and autonomy, SWP demonstrates a generic workflow of initial path planning, constraints classification, path cost values computing, and decisions on path re-planning in the optimization of dynamic constraints. Targeting a real PHP project in Hong Kong, the SWP-enabled constraints optimization service is validated in a BIM environment. The results of this simulation indicate the feasibility of applying this service into practice.

The contributions of this study to the body of knowledge are threefold. Firstly, the architecture of SWP-enabled constraints optimization service can be extended and applied to other constraints improvement. The workflow of this constraint optimization service provides clear steps for other researchers interested in replicating this study. Secondly, while acknowledging the merits of methods in traditional crane path planning and strategies in theoretical robot path planning, this study not only balances the efficiency and path quality but also considers the necessity in path re-planning by employing modified PRM, A*, and *SWP_PathPlanner*. Thirdly, beyond the modeling and monitoring functions supported by SWP, this study argues for the optimization as a new dimension in the constraints management loop which can improve the constraints in a more scientific manner. There are still some future improvements that can be considered in future studies. The continuation of changes in cost values of the path, indicated by the distances between the path and specific constraint, is the only information required in this study. Other sensory information of constraints in real-situation for decision-making and the uncertainty on the cost value of path caused by the sensory noise will be considered in the future study.

**Acknowledgments**

The authors would like to acknowledge the funding agency of this study. The research is sponsored by Start-up Research Project Scheme of the Hong Kong Polytechnic University under Grant Number of 1-ZVL1. It was also funded by the Australian Research Council Discovery Project (grant numbers No. DP180104026) and the National Key R&D Program of

China (No.2016YFC070200504). And it was supported by the Research Institute for Sustainable Urban Development of the Hong Kong Polytechnic University.

## Reference

AlBahnassi, H., & Hammad, A. (2011). Near real-time motion planning and simulation of cranes in construction: framework and system architecture. *Journal of Computing in Civil Engineering, 26*(1), 54-63.

Al Hattab, M., Zankoul, E., Barakat, M., & Hamzeh, F. (2018). Crane overlap and operational flexibility: balancing utilization, duration, and safety. *Construction Innovation, 18*(1), 43-63.

Ali, M. A. D., Babu, N. R., & Varghese, K. (2005). Collision-free path planning of cooperative crane manipulators using a genetic algorithm. *Journal of Computing in Civil Engineering, 19*(2), 182-193.

An, J., Wu, M., She, J., & Terano, T. (2018). Re-optimization strategy for truck crane lift-path planning. *Automation in Construction, 90*, 146-155.

Blackmon, T., Saxena, R., & Song, L. (2011). A conceptual framework for total constraint management in construction. *Proceedings of the 28th ISARC,* 419-424.

Cai, P., Chandrasekaran, I., Zheng, J., & Cai, Y. (2018). Automatic Path Planning for Dual-Crane Lifting in Complex Environments Using a Prioritized Multiobjective PGA. *IEEE Transactions on Industrial Informatics, 14*(3), 829-845.

Chang, Y. C., Hung, W. H., & Kang, S. C. (2012). A fast path planning method for single and dual crane erections. *Automation in Construction, 22,* 468-480.

Chi, H. L., & Kang, S. C. (2010). A physics-based simulation approach for cooperative erection activities. *Automation in Construction, 19*(6), 750-761.

Chi, H. L., Kang, S. C., Hsieh, S. H., & Wang, X. (2014, January). Optimization and Evaluation of Automatic Rigging Path Guidance for Tele-Operated Construction Crane. *In ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 31, p. 1). Vilnius Gediminas Technical University, Department of Construction Economics & Property.

Gong, P., Teng, Y., Li, X., & Luo, L. (2019). Modeling Constraints for the On-Site Assembly Process of Prefabrication Housing Production: A Social Network Analysis. *Sustainability, 11*(5), 1387.

Han, J., & Seo, Y. (2018). Path regeneration decisions in a dynamic environment. *Information Sciences, 450,* 39-52.

Han, S. H., Hasan, S., Bouferguène, A., Al-Hussein, M., & Kosa, J. (2014). Utilization of 3D visualization of mobile crane operations for modular construction on-site assembly. *Journal of Management in Engineering, 31*(5), 04014080.

Housing Authority (2019), Number of Applications and Average Waiting Time for Public Rental Housing, https://www.housingauthority.gov.hk/en/about-us/publications-and-statistics/prh-applications-average-waiting-time/

Hung, W. H., Liu, C. W., Liang, C. J., & Kang, S. C. (2016). Strategies to accelerate the computation of erection paths for construction cranes. *Automation in Construction, 62,* 1-13.

Husdal, J. (2010). A conceptual framework for risk and vulnerability in virtual enterprise networks. In *Managing risk in virtual enterprise networks: implementing supply chain principles* (pp. 1-27). IGI Global.

Kang, S., & Miranda, E. (2006). Planning and visualization for automated robotic crane erection processes in construction. *Automation in Construction, 15*(4), 398-414.

Kang, S. C., & Miranda, E. (2008). Computational methods for coordinating multiple construction cranes. *Journal of Computing in Civil Engineering, 22*(4), 252-263.

Kang, S. C., Chi, H. L., & Miranda, E. (2009). Three-dimensional simulation and visualization of crane assisted construction erection processes. *Journal of Computing in Civil Engineering, 23*(6), 363-371.

Koenig, S., & Likhachev, M. (2005). Fast replanning for navigation in unknown terrain. *IEEE Transactions on Robotics, 21*(3), 354-363.

Lei, Z., Taghaddos, H., Hermann, U., & Al-Hussein, M. (2013a). A methodology for mobile crane lift path checking in heavy industrial projects. *Automation in Construction, 31,* 41-53.

Lei, Z., Taghaddos, H., Olearczyk, J., Al-Hussein, M., & Hermann, U. (2013b). An automated method for checking crane paths for heavy lifts in industrial projects. *Journal of Construction Engineering and Management, 139*(10), 04013011.

Li, X., Shen, G. Q., Wu, P., Fan, H., Wu, H., & Teng, Y. (2017). RBL-PHP: Simulation of Lean Construction and Information Technologies for Prefabrication Housing Production. *Journal of Management in Engineering, 34*(2), 04017053.

Li, X., Shen, G. Q., Wu, P., & Yue, T. (2019). Integrating Building Information Modeling and Prefabrication Housing Production. *Automation in Construction, 100,* 46-60.

Li, C. Z., Xu, X., Shen, G. Q., Fan, C.,Li, X., Hong, J. (2018a). A model for simulating schedule risks in prefabrication housing production: a case study of six-day cycle assembly activities in Hong Kong. *Journal of Cleaner Production, 165,* 10.

Li, C. Z., Xue, F., Li, X., Hong, J., & Shen, G. Q. (2018b). An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction. *Automation in Construction, 89,* 146-161.

Niu, Y., Lu, W., Chen, K., Huang, G. G., & Anumba, C. (2015). Smart construction objects. *Journal of Computing in Civil Engineering, 30*(4), 04015070.

Sivakumar, P. L., Varghese, K., & Babu, N. R. (2003). Automated path planning of cooperative crane lifts using heuristic search. *Journal of Computing in Civil Engineering, 17*(3), 197-207.

Reddy, H. R., & Varghese, K. (2002). Automated path planning for mobile crane lifts. *Computer-Aided Civil and Infrastructure Engineering, 17*(6), 439-448.

Wang, J., Shou, W., Wang, X., & Wu, P. (2016). Developing and evaluating a framework of total constraint management for improving workflow in liquefied natural gas construction. *Construction Management and Economics, 34*(12), 859-874.

Wieland, M., Kaczmarczyk, P., & Nicklas, D. (2008, March). Context integration for smart workflows. In Pervasive Computing and Communications, 2008. PerCom 2008. *Sixth Annual IEEE International Conference on* (pp. 239-242). IEEE.

Wu, Z., Ann, T. W., & Shen, L. (2017). Investigating the determinants of contractor's construction and demolition waste management behavior in Mainland China. *Waste Management, 60,* 290-300.

Yilmaz, N. K., Evangelinos, C., Lermusiaux, P. F., & Patrikalakis, N. M. (2008). Path planning of autonomous underwater vehicles for adaptive sampling using mixed integer linear programming. *IEEE Journal of Oceanic Engineering, 33*(4), 522-537.

Zhang, C., & Hammad, A. (2012). Improving lifting motion planning and re-planning of cranes with consideration for safety and efficiency. *Advanced Engineering Informatics, 26*(2), 396-410.

Zhang, X., Zhao, Y., Deng, N., & Guo, K. (2016). Dynamic path planning algorithm for a mobile robot based on visible space and an improved genetic algorithm. *International Journal of Advanced Robotic Systems, 13*(3), 91.

Zucker, M., Kuffner, J., & Branicky, M. (2007, April). Multipartite RRTs for rapid replanning in dynamic environments. *In Robotics and Automation, 2007 IEEE International Conference on* (pp. 1603-1609). IEEE.